

# Explaining and Sustaining AI Assimilation in Higher Education: The Dual Roles of Engagement and Skeptical Engagement

**Mohammad Islam Biswas**

North South University

**Md. Shamim Talukder**

Universiti Teknologi Brunei

**Dr Muhammad Imran Tanveer Opel**

**Imran.Opel@curtin.edu.au**

Curtin University Sarawak

---

## Article

**Keywords:** AI assimilation, formative writing, skeptical engagement, self-determination theory, human–AI collaboration, higher education

**Posted Date:** October 13th, 2026

**DOI:** <https://doi.org/10.21203/rs.3.rs-10395816/v1>

**License:** © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License. [Read Full License](#)

**Additional Declarations:** No competing interests reported.

---

# Abstract

Although artificial intelligence (AI) is increasingly embedded in higher education, its assimilation into academic writing remains uneven and theoretically underexplored. Drawing on self-determination theory (SDT) and the perceived risk facets model, this study tests an integrated framework of how motivational enablers and risk-based inhibitors jointly shape AI assimilation in formative writing. A sequential multi-method design was used: qualitative analysis of reflective essays from 22 students identified enablers and inhibitors, which informed a survey of 303 students, analysed using partial least squares structural equation modelling (PLS-SEM). Autonomy support, AI empathy, explainability, and perceived fairness foster engagement, whereas technostress, ethical concerns, and loss of control cultivate skeptical engagement, a cautious yet constructive mode of use. Both engagement and skeptical engagement positively predict assimilation, indicating that risk awareness does not suppress adoption but promotes reflective integration. By reconceptualising resistance as skeptical engagement, the study offers a dual-pathway framework explaining how motivation and critical thinking jointly drive AI integration into routine practice, extending motivation and risk theories to AI-mediated learning and yielding implications for autonomy-supportive pedagogy, transparent AI design, and governance that legitimises critical rather than uncritical use.

## 1. Introduction

Artificial intelligence (AI) is reshaping higher education beyond automation, enabling personalised learning, adaptive feedback, and meaningful human–AI interaction (Han et al., 2025). Generative applications, intelligent tutoring, and adaptive writing platforms have enhanced efficiency, creativity, and interaction, and are especially consequential for formative writing, where learners iteratively draft, revise, and receive feedback on their skills (Biswas et al., 2025; Khalifa & Albadawy, 2024). Essays and research papers are central to learning because they push students to reflect and improve, a process now facilitated by AI (Crompton & Burke, 2023; Nguyen et al., 2024). Yet assimilation remains difficult: technological complexity constrains pedagogical alignment, and persistent concerns about privacy, bias, and fairness impede long-term use (An et al., 2024; Chan & Lee, 2025; Zhu et al., 2025). Therefore, explaining how these tools shape learning behaviour and outcomes requires examining both the enablers and the inhibitors of engagement (Kaur & Pavlova, 2026; Luo & Yusuf, 2025).

Two literature streams address assimilation. The enabler stream identifies motivational and design features, usefulness, ease of use, explainability, autonomy, and competence support that enhance trust and engagement (Balaskas et al., 2025; Biswas et al., 2025; Negm, 2026), implying that clear reasoning, fair treatment, and skill-building sustain students' readiness to use AI. The inhibitor stream highlights risks that limit use, technostress, loss of control, ethical concerns, privacy risks, and algorithmic bias (Dalalah & Dalalah, 2023). Students report fatigue from constant updates, unease about being monitored, and doubt about whether AI feedback is fair (Pikhart & Al-Obaydi, 2025; Yu et al., 2025; Zhu et al., 2025). These clusters show that assimilation cannot be reduced to positive system features or user intentions; it is also shaped by how learners cope with and negotiate risk in AI-mediated education.

Despite these advances, prior work has examined enablers and inhibitors largely in isolation, yielding incomplete accounts of assimilation. Assimilation is a higher-order phenomenon involving not just adherence to AI but also the routinisation of its use in daily academic activity, where both positive and negative perceptions shape long-term outcomes (Hina et al., 2025; Sebopelo et al., 2025). Focusing solely on enablers assumes that design improvements alone secure assimilation, whereas inhibitor-focused studies portray risk as a single barrier to adoption (Palash et al., 2022; Talukder et al., 2021). Neither approach captures the dialectical relationship in which enablers and inhibitors coexist, interact, and can even strengthen one another (Talukder et al., 2024). Current models also overlook the quality of human–AI collaboration as a boundary condition, despite growing evidence that the orchestration of partnerships determines whether AI acts as a supportive tutor or a disruptive presence (Kim et al., 2022; Nguyen et al., 2024). These omissions call for theorising and testing a dual-pathway model that integrates enablers, inhibitors, and human–AI collaboration.

This study addresses these gaps by developing a model that synthesises SDT (Ryan & Deci, 2000) and the perceived risk facets perspective (Featherman & Pavlou, 2003) to accommodate both motivational and sceptical determinants of assimilation. Per SDT, autonomy, competence, and relatedness support should encourage sustained engagement and socially responsive feedback (Hannah et al., 2024). Per the risk perspective, technostress, algorithmic bias, loss of control, and ethical risk are likely to trigger skeptical involvement (Guan et al., 2022). Skeptical engagement should be seen not as pure rejection but as an attitude of criticality in which students scrutinize AI-generated work before using it (Kbaier et al., 2025). Skepticism can restrain unreflective use, but it can also be a constructive force promoting more thought and a more considered approach to writing (Glikson & Woolley, 2020; Lapointe & Rivard, 2005). The model further adds AI partnership quality as a moderator, examining whether the translation from engagement or skepticism into assimilation is reinforced or undermined.

This study employed a sequential mixed-methods design of qualitative exploration and quantitative validation. In the qualitative stage, 22 students wrote open-ended essays to inductively identify the enablers and inhibitors shaping their experience of AI in formative writing; this knowledge informed a conceptual model that was subsequently tested in a cross-sectional survey of 303 students using PLS-SEM. The design grounds the model in students' actual experiences while rigorously testing its reliability and explanatory power. The paper makes three contributions. It advances assimilation theory by jointly modelling the facilitators and inhibitors of AI use and explaining how they influence assimilation through both engagement and skeptical engagement. It reframes resistance as skeptical engagement, emphasising that critical reflection and selective use of AI can enhance rather than hinder learning. Finally, it identifies the moderating effect of AI partnership quality, which can foster meaningful assimilation through both engagement and skepticism.

## **2. Background literature**

### **2.1 The enabler–inhibitor perspective**

AI is actively deployed in teaching, assessment, and advising, with generative and adaptive systems especially prominent in formative writing (Cummings et al., 2024; Sperber et al., 2025). These tools offer faster feedback, personalised scaffolding, and reduced workload for students and instructors (Chan & Lee, 2025; Wang et al., 2026). In writing-intensive settings, where students repeatedly draft, receive feedback, and revise, AI can simplify the feedback process and provide specific, skill-building suggestions (Dhillon et al., 2024; Nguyen et al., 2024; Vaccaro et al., 2024), making formative learning a valuable arena for AI's dynamic capabilities (Sperber et al., 2025). The central issue is no longer how many students adopt these tools but how they become assimilated into sustained, meaningful academic routine.

In information systems research, assimilation is the process by which technologies cease to be novel and become a standard aspect of organisational or personal practice (Fosso Wamba, 2022; Swanson, 2004). This distinction is especially significant in the academic domain, where technology use is an ongoing process rather than a one-time event (Flower & Hayes, 1981). Although students can experiment with AI writing assistants or feedback systems, genuine assimilation occurs only when these tools are continually embedded in drafting, revising, and reflecting (Wang, 2025). Assimilation, therefore, emphasises sustained use and routinization, dimensions that adoption models focused only on behavioural intention or initial uptake cannot capture (Orlikowski, 1992).

AI assimilation can be viewed as a socio-technical process shaped by two interconnected forces. On the one hand, enablers such as explainability, fairness, and autonomy foster engagement, trust, and intrinsic motivation, thereby creating favourable conditions for routinization (Memarian & Doleck, 2023; Shin, 2020). On the other hand, inhibitors such as technostress, loss of control, ethical concerns, and algorithmic bias raise doubt and caution, limiting assimilation (Hofmann, 2025; Pikhart & Al-Obaydi, 2025). Research has emphasised positive factors, personalisation, efficiency, and usefulness, while giving comparatively little attention to counterbalancing forces (Shin, 2020; Yang et al., 2025). Pedagogical benefits are also not linear: over-reliance on opaque dialogic tools may undermine critical thinking and

analytical problem-solving when outputs are not transparent (Zerilli et al., 2022). AI's educational value is realised only when it augments rather than substitutes human learning.

The enabler–inhibitor perspective offers a useful lens for investigating this balance (Cenfetelli, 2004; Orlikowski, 1992). It distinguishes factors that facilitate technology use (enablers) from those that uniquely hinder it (inhibitors): enablers may be positively or negatively valenced, whereas inhibitors are unipolar and only deter or limit use (Talukder et al., 2021). Cenfetelli (2004) argues that inhibitors are not merely the absence of enablers but independent constructs requiring separate theoretical treatment—paralleling Herzberg's (1966) two-factor theory, in which satisfaction and dissatisfaction stem from divergent factors, and the conceptual distinction between trust and distrust (Lewicki et al., 1998). Inhibitors such as technostress or algorithmic bias can thus limit adoption even when enablers such as explainability or fairness are present. This study uses the enabler–inhibitor lens to examine how the two jointly influence AI assimilation in higher education.

## 2.2 Self-determination theory (SDT)

SDT (Ryan & Deci, 2000) explains intrinsic motivation and persistence through satisfaction of three needs: autonomy, competence, and relatedness, which, when met, lead learners to internalise goals. In AI-assisted writing, autonomy support lets students set objectives and control strategies; competence support builds mastery by identifying strengths and weaknesses; and relatedness, conceptualised as AI empathy, is the perception that systems are socially sensitive, reducing the isolation of self-regulated writing. The study extends SDT by integrating two design-level enablers, competency building and perceived fairness, as mechanisms that reinforce motivational needs in human–AI collaboration. Competency building offers opportunities to enhance AI literacy and writing self-efficacy, while perceived fairness represents transparent, equitable AI feedback; together they strengthen students' sense of control and legitimacy, expanding SDT to include the ethical and design dimensions of technology-mediated learning. Recent evidence supports SDT in computer-mediated settings: autonomy, competence, and relatedness predict motivation and achievement (Alamer et al., 2025); autonomy support in online environments and AI chatbots increases engagement and self-direction (Chiu et al., 2024; Pan et al., 2025); and enabling environments promote well-being among marginalised students (Dempsey et al., 2025). These results justify SDT as a strong framework for AI assimilation in higher education.

## 2.3 Perceived risk facets model

Whereas SDT captures the motivational drivers of assimilation, risk perceptions also determine whether students participate. Featherman and Pavlou's (2003) model conceptualises risk as a multidimensional construct spanning performance, privacy, financial, time, and social or psychological facets. It has been widely used in technology adoption research to explain hesitation, avoidance, and resistance, recognising that adoption rests not on perceived benefits alone but also on perceived risk and uncertainty (Pavlou, 2003). These risks are especially salient in higher education, where AI is applied to learning outcomes, assessment, and academic identity (Tsamados et al., 2022): students may fear that AI feedback undermines autonomy (psychological risk), gives inaccurate or biased feedback (performance risk), or exposes personal data (privacy risk) (Wang et al., 2025). Such perceptions extend beyond usability and shape whether AI is adopted as a normal part of academic practice.

This study adapts the model to AI-assisted formative writing via the four most applicable inhibitors. Technostress refers to the psychological and temporal risks that arise when the cognitive load of interacting with AI exceeds students' coping capacity, leading to fatigue or avoidance (Wang et al., 2025; Yang et al., 2025). Loss of control reflects psychological and performance risk when opaque or overly directive AI feedback deprives students of autonomy (Krook, 2025). Ethical concerns involve privacy and social risk, concerns that AI violates fairness, confidentiality, or scholarly integrity (An et al., 2024; Zhu et al., 2025). Algorithmic bias entails performance and social risk as students question the neutrality and legitimacy of AI-generated feedback (Chai et al., 2024). Extending prior IS research, these perceived risks are theorised not as obstacles to adoption but as determinants of skeptical engagement, a cautious, critical approach, underscoring that risk awareness need not reduce assimilation but can encourage more responsible AI integration (Kbaier et al., 2025).

## 2.4 Human–AI collaboration in assimilation

Collaborative research shows that system performance depends on interaction quality, not only on technical capability (Jarrahi, 2018; Nguyen et al., 2024). Productive collaboration emerges when AI augments decision-making with transparent, adaptive, goal-aligned support (Shneiderman, 2020); opaque outputs or poor responsiveness undermine trust and use. Assimilation thus depends on enablers, inhibitors, and perceived partnership quality. In academic writing, collaboration defines how students incorporate AI feedback into their process. Quality collaboration lets students receive feedback while retaining agency, control, and ownership of their work (Dhillon et al., 2024; Hina et al., 2025). Clear explanations, adaptive scaffolding, and context-aware feedback allow AI to act as a collaborative tutor that builds trust and interaction (Nguyen et al., 2024; Vaccaro et al., 2024); by contrast, prescriptive or unresponsive feedback can make the system seem intrusive or unreliable, preventing assimilation even among otherwise motivated students (Bahangulu & Owusu-Berko, 2025; Wang et al., 2025). AI partnership quality is therefore positioned as a moderating condition: when collaboration is perceived as successful, engagement is more likely to routinise and skepticism to become a productive force that motivates critical thinking, whereas low partnership quality dampens engagement and can intensify skepticism into distrust or avoidance.

## 3. Research model and hypotheses

### 3.1 Research model

The model posits two antecedent categories: (a) motivational enablers from SDT—autonomy support, competence support, AI empathy, explainability, perceived fairness; and (b) risk-based inhibitors—technostress, loss of control, ethical concerns, algorithmic bias. These operate through two attitudinal pathways: engagement (active, motivated use) and skeptical engagement (cautious, critical, potentially productive use). AI partnership quality moderates whether these translate into assimilation (Fig. 1).

### 3.2 Hypotheses

Autonomy support is the degree to which students perceive the use of AI as self-selected and voluntary rather than imposed (Ryan & Deci, 2000). In AI-facilitated formative writing, this means empowering students to make significant decisions, set goals, customise tasks, and receive personalised feedback, so that they treat AI as a facilitator rather than a barrier when it helps them accomplish tasks efficiently. Per SDT, autonomy satisfaction improves intrinsic motivation, involvement, and sustained learning behaviours (Alamer et al., 2025; Chiu et al., 2024), promoting active rather than passive use and a sense of ownership over one's writing. Autonomy-supportive conditions in AI-enhanced courses increase student satisfaction (Xia et al., 2023), and autonomy combined with competence predicts AI literacy and the use of innovative technologies (Wang, 2025). Although autonomy is well studied in e-learning, its influence on engagement with AI in formative writing remains inadequately investigated. Therefore, we hypothesised that:

*H1: Autonomy support will influence student engagement in formative writing tasks.*

Competency building is the systematic support that helps students become knowledgeable, skilled, and confident in using AI tools for formative writing (Ryan & Deci, 2000). Such support includes adaptive feedback that identifies and explains errors, scaffolded tasks that adjust difficulty, and AI-literacy activities that enable students to interpret and edit AI-generated text (Ryan & Stahl, 2020). Formative tasks such as literature reviews and reflective essays require multiple revisions, yet AI output often addresses only mechanical or surface-level problems and may be implausible against academic standards (Karagoz, 2025). Instructional designs that teach students to verify, edit, and apply AI feedback are therefore essential; students who develop these interpretive and revision skills engage more confidently and persistently

(Mekheimer, 2025; Zhou et al., 2022), whereas without such support, AI output can appear unclear or overwhelming and reduce willingness to use it. Accordingly, we propose the following hypothesis.

*H2: Competency building will influence student engagement with AI tools in formative writing tasks.*

AI empathy is the perception that an AI tutor or assistant is aware of a learner's social needs and offers support, making its replies seem thoughtful, uplifting, and aligned with the learner's emotional state (Srinivasan & San Miguel González, 2022), a design instantiation of SDT relatedness. In academic contexts, conversational agents are increasingly used for feedback, revision, and practice; when they provide socially supportive responses, students are less likely to feel isolated during self-regulated study and more likely to re-engage across drafting, feedback, and improvement cycles (Hew et al., 2023). Satisfying relatedness fosters internalisation, high-quality motivation, and sustained engagement (Ryan & Stahl, 2020), positioning perceived AI empathy as a critical predictor of engagement. Thus, the following hypothesis is proposed.

*H3: AI empathy will influence student engagement in formative writing tasks.*

Explainability is how well an AI system makes its outputs and their underlying reasoning intelligible to users, through explanations, feature attribution, or worked illustration of why a recommendation was generated (Dwivedi et al., 2023; Türkmen, 2024). Students often encounter complex, unfamiliar AI outputs (Biswas et al., 2025); with transparent, practical explanations, they can verify outputs, correct mistakes, and convert feedback into action (Cetinkaya & Krämer, 2025; Er et al., 2025). This indirectly satisfies the need for competence by increasing understanding and restores autonomy by regaining control over decisions (Shin, 2020), thereby supporting intrinsic motivation consistent with SDT (Feldman-Maggor et al., 2025; Nizette et al., 2024). Explainable AI features improve the perceived predictability and credibility of educational tools and raise readiness to adopt them (Feldman-Maggor et al., 2025). Therefore, we formulate the following hypothesis.

*H4: Explainability will influence student engagement with AI tools in formative writing tasks.*

Fairness reflects students' trust in the unbiasedness, equity, and transparency of AI-mediated assessment, feedback, and decision-making (Memarian & Doleck, 2023). In academia, it entails not only equal treatment but also the validity of results and respect for students' positions, concerns that are especially acute where AI offers formative feedback, suggests resources, or grades (Bahangulu & Owusu-Berko, 2025; Chai et al., 2024; Omughelli et al., 2024). When students perceive outcomes as fair, they are more likely to trust the system and invest effort. Understandable AI grading explanations increase perceived fairness and willingness to use (Chai et al., 2024), and encouraging fairness while minimising bias improves student performance and learning outcomes (Omughelli et al., 2024). Its impact on AI-mediated formative writing has not been adequately explored. Thus, we proposed the following hypothesis.

*H5: Perceived fairness will influence student engagement in formative writing tasks.*

Technostress is the psychological pressure that arises when the demands of using technology exceed a person's coping capacity (Wang et al., 2025). Higher education is commonly associated with increased workload, frequent system changes, and perceived digital surveillance, which can cause fatigue, frustration, and disengagement (Yang et al., 2025). These difficulties intensify in formative writing, where learners engage in prolonged drafting, feedback, and revision cycles that require sustained AI contact; rather than treating AI as a collaborator, they may react cautiously and doubt its output (Kbaier et al., 2025). Linked to time, performance, and psychological risk (Featherman & Pavlou, 2003), technostress does not always cause outright rejection but often leads to skeptical interaction, in which students weigh AI's benefits against its limitations. AI-related stress affects perceived utility among students (Zhang & Tong, 2025), so technostress is expected to increase skeptical engagement. Hence, the following hypothesis was formulated.

*H6: Technostress will influence students' skeptical engagement with AI tools in formative writing tasks.*

Loss of control represents psychological and performance risk because it undermines feelings of ownership, competence, and confidence in task outcomes (Featherman & Pavlou, 2003). As systems become more automated and outputs more opaque, a person's ability to monitor and intervene declines (Zerilli et al., 2019), especially consequential in formative writing, where successive feedback and revision are central to skill-building (Dhillon et al., 2024). When students feel excluded from decision-making because AI feedback is prescriptive or too opaque, they grow cautious; rather than rejecting the technology, they tend to become skeptical, critically assessing and selectively implementing recommendations (Kbaier et al., 2025). This matters in higher education because AI feedback can shape revision patterns and evaluative judgments, and prior work shows that system opacity lowers perceived control and trust (Cetinkaya & Krämer, 2025; Sankaran et al., 2021). Loss of control is therefore expected to increase skeptical engagement. Therefore, we propose the following hypothesis.

*H7: Loss of control will influence students' skeptical engagement with AI tools in formative writing tasks.*

Ethical concerns encompass privacy and social-psychological risks related to the protection of sensitive data and the validity of technology-mediated decisions (Featherman & Pavlou, 2003). In formative writing, they extend beyond data safety to concerns about unfair criticism, misuse of personal data, and facilitation of academic dishonesty, such as plagiarism or unauthorised assistance (Al Zaidy, 2024; An et al., 2024). Unless students believe AI systems uphold fairness and academic integrity, their trust declines, and they view AI output more critically rather than accepting it uncritically (Bittle & El-Gayar, 2025; Lund et al., 2025). Ethical risk reduces trust and acceptance of AI in learning (An et al., 2024), and concerns about bias and misuse directly affect willingness to use AI tools (Zhu et al., 2025), so ethical concerns are expected to increase skeptical engagement. The foregoing discussion leads to the following hypothesis:

*H8: Ethical concerns will influence students' skeptical engagement with AI tools in formative writing tasks.*

Algorithmic bias is systematic bias in an AI system that produces unfair or discriminatory results (Kordzadeh & Ghasemaghahi, 2022); students perceive it as systematic inaccuracy or unfairness toward particular groups or writing styles (Shin, 2020). It represents both performance risk—uncertainty about the usefulness and accuracy of feedback—and social risk—fears about unfairness and the validity of assessment (Hasan et al., 2022; Kordzadeh & Ghasemaghahi, 2022). Its consequences are especially serious in academic writing because feedback affects revisions, skill development, and perceptions of fairness in assessment (Baker & Hawn, 2022; Johnson et al., 2022). Because fair evaluation is central to higher education, perceived bias tends to foster skeptical engagement, encouraging students to scrutinise AI feedback critically before use; perceived bias also reduces trust in and willingness to use automated feedback (Chai et al., 2024). Drawing on the preceding arguments, we propose the following hypothesis:

*H9: Algorithmic bias will influence students' skeptical engagement with AI tools in formative writing tasks.*

Engagement in an academic setting means students do not merely use AI superficially but incorporate it deeply into learning, problem-solving, and critical thinking (Fredricks et al., 2004). Cognitively and emotionally engaged students are more inclined to use AI for iterative learning, thereby stabilising its role within the academic process. Engagement has repeatedly been associated with persistence and lower dropout rates, manifestations of lasting learning behaviour, and continued use of learning technologies such as mobile and lifelong-learning apps (Liu & Correia, 2021; Tseng et al., 2022). Despite its established importance, the mediating role of engagement in AI assimilation during formative writing remains underexplored. Building upon the foregoing rationale, we develop the following hypothesis:

*H10: Student engagement will influence AI assimilation in formative writing tasks.*

Skeptical engagement is a critical, evaluative approach in which users do not accept system outputs unquestioningly but instead question, verify, and contextualise them (Vollbrecht, 2022). Unlike resistance, in which interaction is avoided or rejected, skepticism signals readiness to engage while maintaining criticality (Alon-Barkat & Busuioc, 2023). In AI-mediated learning, it takes the form of checking AI feedback, adopting only relevant suggestions, or cross-referencing outputs

against other sources (Mekheimer, 2025). Although such practices slow mindless application, they facilitate more intentional, purposeful use in formative writing. Self-regulated learning research indicates that critical engagement with feedback enhances cognitive investment and persistence (Jones-Jang & Park, 2023), and the IS literature suggests skepticism can complement beneficial use by balancing caution with usefulness (Kbaier et al., 2025; Vollbrecht, 2022). Grounded in iterative improvement, skeptical engagement thus fosters assimilation through critical thinking, learner agency, and conscious deployment of AI. Therefore, the study posits the following hypothesis:

*H11: Skeptical engagement will influence AI assimilation in formative writing tasks.*

AI partnership quality is students' perception of how effectively AI systems collaborate with them toward learning goals (Nguyen et al., 2024). High-quality partnerships feature transparent, responsive, goal-focused interaction in which AI provides meaningful support, and students retain control over academic choices (Vaccaro et al., 2024); poor partnerships, marked by misaligned assistance, low responsiveness, or overreliance on automated output, undermine trust and reduce meaningful engagement (Holstein et al., 2023). Perceived quality preconditions students' attitudes toward assimilation. With a high-quality partner, engagement is more likely to lead to durable, routinised use, and successful collaboration can transform skeptical engagement into a constructive orientation that lets students engage critically and selectively without disengaging. Conversely, a low-quality partnership can undermine the benefits of engagement and heighten skepticism-related uncertainty, limiting assimilation. Effective human–AI cooperation outperforms either alone (Vaccaro et al., 2024), and perceived partnership quality raises students' readiness to incorporate AI into academic work (Nguyen et al., 2024). Accordingly, we formulate the following hypothesis:

*H12a: AI partnership quality will moderate the relationship between engagement and AI assimilation.*

*H12b: AI partnership quality will moderate the relationship between skeptical engagement and AI assimilation.*

## 4. Methods

A sequential multi-method design combined a qualitative study with a cross-sectional survey, well-suited to the emerging theory of AI assimilation in formative writing. The qualitative phase probed students' experiences, revealing enablers and inhibitors and prompting construct refinement, notably reconceptualising resistance as skeptical engagement, while the quantitative phase tested relationships among engagement, skeptical engagement, and assimilation (Hina et al., 2025; Nguyen et al., 2024).

### 4.1 Qualitative study

The qualitative phase examined students' experiences and perceptions of AI in formative writing, as well as the conditions that facilitate or impede assimilation. Open-ended essays encouraged deep reflection and minimised interviewer influence (Hoffmann, 2007; Strauss & Corbin, 1998), a method well suited to exploratory study of emerging educational technologies because it yields rich, self-directed accounts. Respondents came from two universities where AI writing assistants (ChatGPT, Gemini, Grammarly, Turnitin Draft Coach) were embedded in coursework; prior AI writing experience was required and screened. Of 25 invited, 24 returned essays; two were excluded for insufficient detail, yielding 22 undergraduate and postgraduate participants across business/management, computing/IT, and education/humanities, diverse in discipline but sharing a common teaching environment (Appendix A). The sample meets the thematic saturation norm of 20–30 participants (Guest et al., 2020).

Participants wrote 400–600-word essays on four prompts: (a) advantages and disadvantages of AI in writing; (b) trust, explainability, and fairness of feedback; (c) emotional and motivational responses; and (d) readiness for future use (Corbin & Strauss, 2015). A key insight was that students framed AI use not as acceptance or rejection but as critical, discriminating use, questioning, verifying, and selectively applying feedback while retaining control, theorised as skeptical

engagement. Engagement and skeptical engagement were derived inductively; AI partnership quality, absent from the narratives, was theorised during model development from collaboration research (Hina et al., 2025; Nguyen et al., 2024).

## 4.2 Data coding and analysis

Essays underwent grounded-theory coding through open, axial, and selective cycles (Corbin & Strauss, 2015). Open coding by two researchers yielded first-order codes (e.g., "how much AI feedback to use" [autonomy], "constant checking is exhausting" [technostress], "AI prefers a Western style" [bias]). Axial coding grouped these into five enabler clusters (autonomy support, competence building, AI empathy, explainability, fairness; Appendix B), four inhibitor clusters (technostress, loss of control, ethical concerns, algorithmic bias), and a cooperation dimension (responsiveness, complementarity, trust calibration) reflecting partnership quality. Selective coding converged enablers into engagement and inhibitors into skeptical engagement. Coding achieved 87% intercoder agreement, with discrepancies resolved through recursive discussion (Gligor & Autry, 2012) and analytic memos documenting decisions; saturation was reached after roughly 20 essays.

## 4.3 Quantitative study

A cross-sectional survey tested the model. Convenience sampling was limited to students with direct experience using AI in formative writing (Stratton, 2023), ensuring relevant exposure (Golzar et al., 2022). Hard-copy questionnaires were administered in classroom sessions at several universities actively using AI, raising response rates and completeness. Of 320 administered, 303 were usable (94.69%), spanning undergraduate and postgraduate students across disciplines (Appendix C), exceeding the recommended PLS-SEM minimum of 200 (Hair et al., 2019). Data collection was conducted with ethics approval; respondents gave voluntary, informed consent, were assured of confidentiality and the right to withdraw, and all data were anonymised before analysis.

## 4.4 Measures

Measures were adapted from prior literature, contextualised for AI-assisted formative writing, and captured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Enablers: autonomy support (4 items; Ryan & Deci, 2000; Annamalai et al., 2025); competence building (3 items; Chiu et al., 2025; Olafsen et al., 2025); AI empathy (4 items; Olafsen et al., 2025; Srinivasan & San Miguel González, 2022); explainability and fairness (4 items each; Shin, 2020; Zhu et al., 2025). Inhibitors: technostress (4 items; Chukwuere & Chukwuere, 2025); loss of control (4 items; Rosenbacke et al., 2024); ethical concerns (3 items; Yu et al., 2025; Dong et al., 2025); algorithmic bias (4 items; Chai et al., 2024). Engagement (3 items; Al Zaidy, 2024; Hannah et al., 2024) and skeptical engagement (3 items; Lapointe & Rivard, 2005; Vollbrecht, 2022); AI partnership quality (3 items; Hina et al., 2025); AI assimilation (3 items; Hina et al., 2025; Sebopelo et al., 2025). Full items appear in Appendix D. Content validity was established by a panel of three experts in educational technology and higher-education pedagogy, who reviewed all items; minor wording revisions improved clarity and contextual alignment. A pilot test with 30 students confirmed internal consistency (all Cronbach's  $\alpha$  values above 0.70; Hair et al., 2019), and construct reliability and validity were further supported by confirmatory factor analysis, thereby rendering the instrument suitable for large-scale data collection.

## 5. Results

### 5.1 Qualitative results

Thematic analysis produced ten second-order categories, which were abstracted into six higher-order themes: motivational enablers, design enablers, technological barriers, ethical concerns, bias and trust issues, and human–AI collaboration. These show how experiences produced two attitudinal responses, engagement and skeptical engagement, that shaped assimilation.

## 5.1.1 Motivational enablers

Students valued autonomy: “I like that I can decide whether to use the AI's suggestion or not. It feels like I am still in charge of my writing” (P7), consistent with SDT (Ryan & Deci, 2000). Competence-building feedback improved skills: “The AI showed me weaknesses in my argument and explained why, which helped me improve more than just getting a grade” (P5), echoing evidence that adaptive feedback enhances self-efficacy (Chiu et al., 2025). Empathy motivated revision: “The way the system responded almost felt like a tutor cheering me on. It kept me motivated to revise my draft” (P3), suggesting socially attuned responses strengthen relatedness (Srinivasan & San Miguel González, 2022).

## 5.1.2 Design enablers

Transparency built trust: “When I know why it recommends a change, I trust it more” (P9), consistent with XAI research (Türkmen, 2024); opacity bred suspicion: “It flagged my paragraph as unclear but didn't explain why. That made me doubt the tool” (P14). Fairness raised willingness to engage: “The AI's feedback felt fair and unbiased, which made me take it seriously” (P18), aligning with evidence that fairness increases legitimacy (Chai et al., 2024).

## 5.1.3 Technological barriers

Technostress includes overload, fatigue, surveillance, and was widely reported: “It's tiring to always check if the AI is right or wrong. Sometimes it feels easier not to use it at all” (P2), consistent with links to poorer learning attitudes (Yang et al., 2025). Rather than abandoning tools, most students became selective, verifying recommendations before use. Loss of control mattered when feedback was prescriptive: “The tool kept auto-correcting my sentences, and I felt like my own ideas were being pushed aside” (P10), echoing automation-bias concerns that opaque systems diminish agency (Rosenbacke et al., 2024).

## 5.1.4 Ethical concerns

Students raised concerns about privacy, fairness, and integrity. Data handling worried them: “I don't know where my essays go after I upload them. That feels risky” (P8), and some flagged misconduct risk: “If students just copy whatever it gives, that's basically cheating” (P15) (An et al., 2024; Zhu et al., 2025). Rather than abandoning AI, students took a skeptical, responsibility-focused stance: “I'll take its suggestions, but I always rewrite them in my own words, just to be safe” (P19), treating AI as a secondary source.

## 5.1.5 Bias and trust issues

Students distrusted feedback objectivity: “It seems to prefer a very Western style of writing. That makes me wonder if it's biased” (P13), and noted inconsistency: “Sometimes it praises my introduction, and the next time it says it's weak, even though I didn't change much” (P20), consistent with evidence that perceived bias erodes trust (Chai et al., 2024). A few normalised bias (“Professors are also biased... maybe AI is just another version of that,” P11), but most responded with heightened criticality and selective use.

## 5.1.6 Human–AI collaboration

Students who saw AI as a partner spoke positively: “The AI gave me ideas, but I still had to refine them. Together it worked well” (P8) (Hina et al., 2025; Vaccaro et al., 2024), whereas uneven collaboration bred frustration: “Sometimes it feels like I'm fighting the AI rather than working with it” (P17). Partnership quality thus acts as a moderator: strong collaboration mitigates inhibitors, weak collaboration undermines even effective enablers. Overall, motivational and design enablers drove engagement; technological, ethical, and bias barriers drove skeptical engagement; and partnership quality conditioned whether these became assimilation.

## 5.2 Quantitative results

### 5.2.1 Non-response and common method bias

Non-response bias was assessed by comparing early and late respondents (first and last quartiles,  $n = 75$  each; Armstrong & Overton, 1977): no significant differences emerged (age,  $t(148) = -1.75$ ,  $p = .082$ ; gender,  $\chi^2(1) = 2.21$ ,  $p = .137$ ; discipline,  $\chi^2(3) = 1.05$ ,  $p = .789$ ; all five key construct means,  $p \geq .229$ ). For common method bias, Harman's single-factor test yielded a first unrotated factor of 18.4% (below 50%; Podsakoff et al., 2003), and a full collinearity test (Kock, 2015) produced VIFs of 1.30–1.91 (below 3.30). Neither bias is a material concern.

## 5.2.2 Measurement model

Reliability and validity were evaluated via indicator loadings, Cronbach's  $\alpha$ , composite reliability (CR), and average variance extracted (AVE) (Table 1). All loadings exceeded 0.70 (Hair et al., 2019);  $\alpha$  ranged 0.725–0.842, CR 0.844–0.894, and AVE 0.623–0.692, all above the 0.50 threshold (Fornell & Larcker, 1981), confirming reliability, convergent validity, and unidimensionality.

Table 1  
Internal consistency and convergent validity.

| Construct                                                                                        | Item | Loading | VIF   | $\alpha$ | CR    | AVE   |
|--------------------------------------------------------------------------------------------------|------|---------|-------|----------|-------|-------|
| Algorithmic Bias                                                                                 | AB1  | 0.842   | 1.858 | 0.831    | 0.887 | 0.662 |
|                                                                                                  | AB2  | 0.800   | 1.654 |          |       |       |
|                                                                                                  | AB3  | 0.816   | 1.831 |          |       |       |
|                                                                                                  | AB4  | 0.796   | 1.791 |          |       |       |
| AI Empathy                                                                                       | AE1  | 0.805   | 1.669 | 0.826    | 0.884 | 0.656 |
|                                                                                                  | AE2  | 0.839   | 1.865 |          |       |       |
|                                                                                                  | AE3  | 0.805   | 1.740 |          |       |       |
|                                                                                                  | AE4  | 0.791   | 1.709 |          |       |       |
| AI Assimilation                                                                                  | AIA1 | 0.823   | 1.531 | 0.752    | 0.858 | 0.669 |
|                                                                                                  | AIA2 | 0.808   | 1.480 |          |       |       |
|                                                                                                  | AIA3 | 0.823   | 1.519 |          |       |       |
| Autonomy Support                                                                                 | AS1  | 0.879   | 1.704 | 0.824    | 0.878 | 0.645 |
|                                                                                                  | AS2  | 0.805   | 1.866 |          |       |       |
|                                                                                                  | AS3  | 0.795   | 1.909 |          |       |       |
|                                                                                                  | AS4  | 0.726   | 1.568 |          |       |       |
| Competency Building                                                                              | CB1  | 0.818   | 1.434 | 0.725    | 0.844 | 0.643 |
|                                                                                                  | CB2  | 0.797   | 1.360 |          |       |       |
|                                                                                                  | CB3  | 0.791   | 1.521 |          |       |       |
| Ethical Concerns                                                                                 | EC1  | 0.869   | 1.789 | 0.777    | 0.870 | 0.692 |
|                                                                                                  | EC2  | 0.800   | 1.533 |          |       |       |
|                                                                                                  | EC3  | 0.824   | 1.577 |          |       |       |
| Engagement                                                                                       | ENG1 | 0.801   | 1.462 | 0.761    | 0.863 | 0.677 |
|                                                                                                  | ENG2 | 0.843   | 1.623 |          |       |       |
|                                                                                                  | ENG3 | 0.824   | 1.566 |          |       |       |
| Explainability                                                                                   | EX1  | 0.821   | 1.724 | 0.816    | 0.879 | 0.644 |
|                                                                                                  | EX2  | 0.794   | 1.705 |          |       |       |
|                                                                                                  | EX3  | 0.822   | 1.740 |          |       |       |
|                                                                                                  | EX4  | 0.772   | 1.607 |          |       |       |
| Fairness                                                                                         | FA1  | 0.752   | 1.547 | 0.799    | 0.868 | 0.623 |
|                                                                                                  | FA2  | 0.790   | 1.549 |          |       |       |
|                                                                                                  | FA3  | 0.781   | 1.656 |          |       |       |
| Note: $\alpha$ = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. |      |         |       |          |       |       |

| Construct                                                                                        | Item | Loading | VIF   | $\alpha$ | CR    | AVE   |
|--------------------------------------------------------------------------------------------------|------|---------|-------|----------|-------|-------|
| Loss of Control                                                                                  | FA4  | 0.831   | 1.674 | 0.842    | 0.894 | 0.678 |
|                                                                                                  | LC1  | 0.828   | 1.915 |          |       |       |
|                                                                                                  | LC2  | 0.824   | 1.801 |          |       |       |
|                                                                                                  | LC3  | 0.805   | 1.813 |          |       |       |
|                                                                                                  | LC4  | 0.836   | 1.844 |          |       |       |
| AI Partnership Quality                                                                           | PQ1  | 0.885   | 1.723 | 0.803    | 0.869 | 0.691 |
|                                                                                                  | PQ2  | 0.712   | 1.721 |          |       |       |
|                                                                                                  | PQ3  | 0.885   | 1.741 |          |       |       |
| Skeptical Engagement                                                                             | SE1  | 0.807   | 1.494 | 0.750    | 0.857 | 0.666 |
|                                                                                                  | SE2  | 0.838   | 1.497 |          |       |       |
|                                                                                                  | SE3  | 0.802   | 1.511 |          |       |       |
| Technostress                                                                                     | TS1  | 0.811   | 1.796 | 0.827    | 0.885 | 0.659 |
|                                                                                                  | TS2  | 0.812   | 1.711 |          |       |       |
|                                                                                                  | TS3  | 0.814   | 1.784 |          |       |       |
|                                                                                                  | TS4  | 0.809   | 1.701 |          |       |       |
| Note: $\alpha$ = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. |      |         |       |          |       |       |

### 5.2.3 Discriminant validity

Discriminant validity was confirmed using the heterotrait–monotrait ratio (HTMT; Table 2). The highest value was 0.696 (autonomy support–engagement), below the 0.85 threshold (Henseler et al., 2015), establishing discriminant validity across all pairs and confirming the adequacy of the measurement model.

Table 2  
Heterotrait–monotrait ratio (HTMT) matrix.

| AB                                                                                                                                                                                                                                                                                                         | AB    | AE    | AS    | AIA   | CB    | EC    | ENG   | EX    | FA    | LC    | PQ    | SE    | TS |
|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|----|
|                                                                                                                                                                                                                                                                                                            |       |       |       |       |       |       |       |       |       |       |       |       |    |
| AE                                                                                                                                                                                                                                                                                                         | 0.243 |       |       |       |       |       |       |       |       |       |       |       |    |
| AS                                                                                                                                                                                                                                                                                                         | 0.208 | 0.336 |       |       |       |       |       |       |       |       |       |       |    |
| AIA                                                                                                                                                                                                                                                                                                        | 0.067 | 0.364 | 0.350 |       |       |       |       |       |       |       |       |       |    |
| CB                                                                                                                                                                                                                                                                                                         | 0.170 | 0.269 | 0.363 | 0.222 |       |       |       |       |       |       |       |       |    |
| EC                                                                                                                                                                                                                                                                                                         | 0.337 | 0.192 | 0.303 | 0.061 | 0.285 |       |       |       |       |       |       |       |    |
| ENG                                                                                                                                                                                                                                                                                                        | 0.289 | 0.593 | 0.696 | 0.593 | 0.443 | 0.251 |       |       |       |       |       |       |    |
| EX                                                                                                                                                                                                                                                                                                         | 0.206 | 0.327 | 0.384 | 0.372 | 0.412 | 0.198 | 0.542 |       |       |       |       |       |    |
| FA                                                                                                                                                                                                                                                                                                         | 0.266 | 0.314 | 0.357 | 0.262 | 0.374 | 0.198 | 0.508 | 0.277 |       |       |       |       |    |
| LC                                                                                                                                                                                                                                                                                                         | 0.374 | 0.187 | 0.231 | 0.059 | 0.226 | 0.472 | 0.193 | 0.173 | 0.258 |       |       |       |    |
| PQ                                                                                                                                                                                                                                                                                                         | 0.086 | 0.225 | 0.046 | 0.055 | 0.049 | 0.128 | 0.062 | 0.052 | 0.062 | 0.038 |       |       |    |
| SE                                                                                                                                                                                                                                                                                                         | 0.354 | 0.113 | 0.228 | 0.318 | 0.192 | 0.531 | 0.166 | 0.149 | 0.118 | 0.557 | 0.063 |       |    |
| TS                                                                                                                                                                                                                                                                                                         | 0.361 | 0.216 | 0.267 | 0.097 | 0.102 | 0.370 | 0.267 | 0.145 | 0.188 | 0.441 | 0.096 | 0.607 |    |
| <i>Note: AS = Autonomy Support; CB = Competency Building; AE = AI Empathy; EX = Explainability; FA = Fairness; TS = Technostress; LC = Loss of Control; EC = Ethical Concerns; ENG = Engagement; SE = Skeptical Engagement; PQ = AI Partnership Quality; AIA = AI Assimilation; AB = Algorithmic Bias.</i> |       |       |       |       |       |       |       |       |       |       |       |       |    |

## 5.2.4 Structural model

The structural model was assessed using bootstrapping in SmartPLS 4 (5,000 resamples), with  $R^2$ ,  $Q^2$ , RMSE, and MAE to evaluate explanatory and predictive power (Hair et al., 2021). It explained moderate variance in engagement ( $R^2 = 0.532$ ,  $Q^2 = 0.513$ ) and weaker variance in skeptical engagement ( $R^2 = 0.360$ ,  $Q^2 = 0.339$ ) and assimilation ( $R^2 = 0.308$ ,  $Q^2 = 0.194$ ). Positive  $Q^2$  values confirm predictive relevance; RMSE/MAE (Engagement 0.703/0.569; Skeptical Engagement 0.819/0.645; Assimilation 0.905/0.717) indicate acceptable accuracy. Autonomy support ( $\beta = 0.418$ ,  $t = 11.436$ ,  $p < 0.001$ ), AI empathy ( $\beta = 0.254$ ,  $t = 6.104$ ,  $p < 0.001$ ), explainability ( $\beta = 0.177$ ,  $t = 4.108$ ,  $p < 0.001$ ), and fairness ( $\beta = 0.159$ ,  $t = 3.876$ ,  $p < 0.001$ ) significantly increased engagement, whereas competency building did not ( $\beta = 0.053$ ,  $t = 1.312$ ,  $p = 0.190$ ). Among inhibitors, technostress ( $\beta = 0.319$ ,  $t = 6.592$ ,  $p < 0.001$ ), loss of control ( $\beta = 0.232$ ,  $t = 4.061$ ,  $p < 0.001$ ), and ethical concerns ( $\beta = 0.209$ ,  $t = 4.109$ ,  $p < 0.001$ ) significantly increased skeptical engagement; algorithmic bias did not ( $\beta = 0.059$ ,  $t = 1.296$ ,  $p = 0.195$ ). Both pathways predicted assimilation: engagement ( $\beta = 0.484$ ,  $t = 10.842$ ,  $p < 0.001$ ) and skeptical engagement ( $\beta = 0.295$ ,  $t = 5.965$ ,  $p < 0.001$ ). AI partnership quality did not moderate the engagement–assimilation path ( $\beta = 0.062$ ,  $t = 1.145$ ,  $p = 0.252$ ) but significantly moderated the skeptical engagement–assimilation path ( $\beta = 0.127$ ,  $t = 2.104$ ,  $p = 0.035$ ). Table 3 reports the results. Figure 2 shows that the left panel (H12a) shows near-parallel slopes, consistent with the non-significant interaction; the right panel (H12b) shows a steeper slope under high PQ, indicating that partnership quality strengthens the positive effect of skeptical engagement on assimilation.

Table 3  
Structural model results.

| No.                                                          | Path           | $\beta$ | t      | p       | 95% CI     | Supported | R <sup>2</sup> | Q <sup>2</sup> | RMSE  | MAE  |
|--------------------------------------------------------------|----------------|---------|--------|---------|------------|-----------|----------------|----------------|-------|------|
| H1                                                           | AS → ENG       | 0.42    | 11.436 | < 0.001 | 0.34–0.49  | Yes       | 0.53           | 0.51           | 0.703 | 0.57 |
| H2                                                           | CB → ENG       | 0.05    | 1.312  | 0.19    | −0.03–0.13 | No        |                |                |       |      |
| H3                                                           | AE → ENG       | 0.25    | 6.104  | < 0.001 | 0.17–0.34  | Yes       |                |                |       |      |
| H4                                                           | EX → ENG       | 0.18    | 4.108  | < 0.001 | 0.09–0.26  | Yes       |                |                |       |      |
| H5                                                           | FA → ENG       | 0.16    | 3.876  | < 0.001 | 0.08–0.24  | Yes       |                |                |       |      |
| H6                                                           | TS → SE        | 0.32    | 6.592  | < 0.001 | 0.22–0.41  | Yes       | 0.36           | 0.34           | 0.819 | 0.65 |
| H7                                                           | LC → SE        | 0.23    | 4.061  | < 0.001 | 0.12–0.34  | Yes       |                |                |       |      |
| H8                                                           | EC → SE        | 0.21    | 4.109  | < 0.001 | 0.11–0.30  | Yes       |                |                |       |      |
| H9                                                           | AB → SE        | 0.06    | 1.296  | 0.195   | −0.03–0.15 | No        |                |                |       |      |
| H10                                                          | ENG → AIA      | 0.48    | 10.842 | < 0.001 | 0.39–0.57  | Yes       | 0.31           | 0.19           | 0.905 | 0.72 |
| H11                                                          | SE → AIA       | 0.30    | 5.965  | < 0.001 | 0.19–0.39  | Yes       |                |                |       |      |
| H12a                                                         | PQ × ENG → AIA | 0.06    | 1.145  | 0.252   | −0.04–0.17 | No        |                |                |       |      |
| H12b                                                         | PQ × SE → AIA  | 0.13    | 2.104  | 0.035   | 0.02–0.25  | Yes       |                |                |       |      |
| Note: Abbreviations as in Table 2. CI = confidence interval. |                |         |        |         |            |           |                |                |       |      |

## 6. Discussion

Autonomy support most strongly influenced engagement ( $\beta = 0.418$ ), followed by AI empathy ( $\beta = 0.254$ ), explainability ( $\beta = 0.177$ ), and fairness ( $\beta = 0.159$ ), while competency building had no significant effect ( $\beta = 0.053$ ,  $p = .190$ ). This supports SDT (Ryan & Deci, 2000): AI that promotes autonomy, competence, and relatedness through clear, fair design fosters engagement whose effects run deeper than the other design features tested. That autonomy carried roughly 1.6 times the weight of the next-strongest predictor suggests students respond most to systems that preserve their sense of control over the writing process, ahead of the tool's perceived empathy or transparency. Explainable and fair feedback still enhanced trust and perceived legitimacy, consistent with prior work (Chai et al., 2024; Feldman-Maggor et al., 2025), but more modestly than autonomy or empathy. The null effect for competency building indicates that most AI writing systems remain geared toward mechanical correction rather than higher-order scaffolding; since surface feedback does not register as pedagogically valuable (Li, 2025), these features may need to shift toward adaptive, metacognitive feedback to support authentic learning and sustained assimilation.

Among the inhibitors, technostress showed the strongest association with skeptical engagement ( $\beta = 0.319$ ), followed by loss of control ( $\beta = 0.232$ ) and ethical concerns ( $\beta = 0.209$ ); algorithmic bias had no significant effect ( $\beta = 0.059$ ,  $p = .195$ ). This aligns with the perceived risk facets model (Featherman & Pavlou, 2003): psychological and performance risks prompt caution, with the sheer cognitive and emotional burden of managing AI tools mattering more than either autonomy loss or moral discomfort. This is not an unfavourable outcome. It produced skeptical engagement, a critical stance in which students weighed AI feedback before accepting it, extending prior work on technology resistance by showing that skepticism can function as a productive mode of engagement that sharpens evaluative judgment and responsible use (Kbaier et al., 2025; Vollbrecht, 2022). The null effect of algorithmic bias suggests students may treat it as an unavoidable feature of evaluative systems, registering concern only when bias becomes visibly unfair or inaccurate (Bahangulu & Owusu-Berko, 2025; Kordzadeh & Ghasemaghaei, 2022).

Both attitudinal pathways predicted assimilation, though to different degrees. Engagement was the stronger route ( $\beta = 0.484$ ), exerting roughly 1.6 times the influence of skeptical engagement ( $\beta = 0.295$ ), confirming that motivation and critical reflection both sustain continued AI use, with enthusiasm carrying more weight than caution. Students who were both actively engaged and appropriately skeptical were more likely to build AI into their writing habits, supporting a dual-pathway model in which sustained use draws on affective and evaluative routes simultaneously rather than either alone (Al Zaidy, 2024; Kbaier et al., 2025).

AI partnership quality did not moderate the engagement–assimilation relationship ( $\beta = 0.062$ ,  $p = .252$ ): students with positive engagement appear to carry that motivation into assimilation regardless of how they judge the quality of their partnership with the tool (Atchley et al., 2024; Razmerita, 2024). It did, however, moderate the skeptical engagement–assimilation relationship in a strengthening rather than suppressing direction ( $\beta = 0.127$ ,  $p = .035$ ): skepticism converted into assimilation more readily, not less, when students perceived the partnership as responsive and cooperative (Hoffman et al., 2023; Li et al., 2024). When partnership quality is high, critical evaluation and continued use are not in tension, students can assess AI output on its merits while still incorporating the tool into their academic work (Shneiderman, 2020). Taken together, assimilation depends less on usability or motivation alone than on whether human–AI collaboration lets students maintain trust and critical agency simultaneously (Nguyen et al., 2024; Razmerita, 2024; Shneiderman, 2020).

## 6.1 Theoretical implications

This study contributes to knowledge on AI assimilation in higher education by synthesising motivational, design, and risk-based approaches into a coherent socio-technical framework. Rather than treating AI adoption as a dichotomous outcome, it shows that sustained assimilation stems from a combination of enabling conditions, perceived risks, and the nature of human–AI interaction. In doing so, it reorients information systems research from initial acceptance toward the attitudinal processes that regulate long-term use in learning contexts.

First, the study challenges the prevailing assumption in risk-based adoption models that perceived risk is the main cause of avoidance or rejection. Extending the perceived risk facets model (Featherman & Pavlou, 2003), it identifies skeptical engagement as a distinct attitudinal response to risk: rather than becoming unresponsive, students reacted to uncertainty by critically validating, filtering, and selectively applying AI feedback. This builds on risk theory by showing that risk awareness can lead to reflective, self-regulated use rather than inhibiting it, bridging behavioural frameworks of technology use and attitudinal perspectives that recognise learner agency in human–AI interaction. Second, it extends SDT by showing psychological-need satisfaction can be facilitated by system design, not only human interaction (Shneiderman, 2020; Wang et al., 2024): explainability and fairness supported autonomy and competence by making feedback intelligible and legitimate, and AI empathy operationalised relatedness as technologically mediated support (Martin & Waldman, 2023), situating SDT within socio-technical systems.

Third, it advances assimilation theory by proposing a dual pathway in which engagement and skeptical engagement both contribute to sustained use, challenging adoption-based frameworks (TAM, UTAUT) that essentially conflate positive motivation with continuance (Davis, 1989; Venkatesh et al., 2003). Enthusiasm and trust, along with careful and evaluative participation, can enhance long-term assimilation (Hoffman et al., 2023; von Zahn et al., 2025); by modelling these pathways simultaneously, the study offers a more detailed explanation of post-adoption behaviour in AI-supported learning (Bhattacharjee, 2001; Limayem et al., 2003). Finally, the asymmetric moderation redefines skepticism as a potentially beneficial orientation rather than an obstacle (Okamura & Yamada, 2020): consistent with calibrated-trust research, high-quality partnerships let users preserve critical agency while integrating AI into routine (Rai et al., 2019; Shin, 2021), shifting IS theory from presumed unconditional trust toward context-sensitive processes promoting responsible use (Dennehy et al., 2023; Glikson & Woolley, 2020).

## 6.2 Practical implications

The findings of this study provide actionable guidance for educators, system designers, and policymakers seeking to deploy AI in formative writing in a responsible pedagogical way. The primary implication is that skepticism towards AI should be viewed as a learning orientation, which is productive to work with rather than an obstacle (Kbaier et al., 2025). Students frequently verified, questioned, and selectively applied AI feedback, and this skeptical interaction positively influenced assimilation (Shneiderman, 2020). Educators can use this strategy to incorporate systematic reflective tasks, including revision/justification statements, in which students must provide a reason for their choice or for rejecting certain AI recommendations. This leads to the development of skepticism into metacognition, thereby strengthening critical thinking and academic integrity. This strategy aligns with research in formative assessment, which indicates that explicit reasoning led to higher learning quality and persistence (Nicol & Macfarlane-Dick, 2006; Teng & Yue, 2023).

Autonomy support was found as a powerful motivator of engagement, highlighting the importance of enabling students to control the learning objectives, the learning pace, and the degree of AI support (Ryan & Stahl, 2020). Simultaneously, the learner's perception of loss of control suggests that over-automation may decrease students' sense of ownership (Shneiderman, 2020). Teachers are thus encouraged to be both flexible and structured by incorporating decision checkpoints that ask learners to explain how AI feedback influenced their changes. The practices are consistent with self-determination theory, which links autonomy to intrinsic motivation and long-term engagement (Ryan & Stahl, 2020). The non-significant effect of competency building also indicates that most existing AI tools focus on surface-level correction rather than intensive writing development (McCarthy et al., 2022). Higher-order skills such as argument coherence, evidence integration, and reasoning refinement should be prioritized by developers and institutions (Butterfuss et al., 2022). Explanatory and strategic feedback have been shown in previous studies to produce greater learning transfer than mechanical correction alone (McCarthy et al., 2022; Teng & Yue, 2023).

Design-level implications are equally relevant. Student perceptions of fairness and transparency on AI systems increased student engagement and trust, whereas opacity and inconsistency declined trust. Thus, designers ought to explain the explainability characteristics that justify the feedback, as well as the constraints of AI feedback and fairness systems, in sufficient detail to ensure consistency across drafts and writing styles (Teng & Yue, 2023). These design principles have been shown to increase trust and facilitate the further application of AI in education (Chai et al., 2024; Feldman-Maggor et al., 2025).

Lastly, the substantial moderating effect of AI partnership quality highlights the importance of effective assimilation informed by students' experiences working with AI. High-quality partnerships played a vital role in translating skeptical engagement into beneficial and sustained use rather than merely intensifying the impacts of positive engagement. When AI was seen as a supportive partner and not an authoritative competitor, skepticism was fruitful and led to accountable incorporation. Educators must then position AI as an assistant tutor and be specifically trained in how to provide AI-enhanced tasks (McCarthy et al., 2022; Teng & Yue, 2023). At the institutional level, faculty development programs and explicit governance policies are needed to ensure that engagement and skepticism are translated into responsible, ethical, and sustainable AI applications in higher education.

## 7. Limitations and future research

Several limitations delimit the findings. First, the qualitative stage drew on 22 essays from two universities. Although saturation was achieved, the institutional and cultural scope limits transferability. Replication across universities, disciplines, and national contexts is needed. Second, the quantitative design was cross-sectional and self-reported; perceived engagement and assimilation may not correspond exactly to observed behaviour. Longitudinal studies, experiments, and learning analytics approaches could assess how skeptical engagement develops and whether it produces durable changes in AI use. Third, skeptical engagement was measured with modified items originally focused on resistance. The scale captured the evaluative behaviour observed qualitatively, but may not fully represent the construct.

Future research should develop and validate a dedicated skeptical-engagement measure and test its relationships across writing tasks and other educational uses of AI.

## 8. Conclusion

This study explains AI assimilation in formative writing through two complementary attitudinal pathways. Autonomy support, AI empathy, explainability, and fairness increased engagement, whereas technostress, loss of control, and ethical concerns increased skeptical engagement. Competency building and algorithmic bias were nonsignificant predictors of their respective pathways. Both engagement and skeptical engagement predicted assimilation, with engagement exerting the larger effect. AI partnership quality did not moderate positive engagement but strengthened the skeptical engagement-assimilation relationship. The qualitative findings reinforce the interpretation: students commonly continued to use AI while questioning, verifying, and selectively applying its outputs. The central implication is that responsible AI assimilation does not require the removal of skepticism. Instead, critical evaluation can help students retain agency as they incorporate AI into routine academic practice. Effective pedagogy, transparent and fair design, and governance that accommodates critical use can therefore support assimilation without encouraging unreflective dependence.

## Declarations

### Data availability statement

The de-identified quantitative dataset and SmartPLS results are available to editors and referees as supplementary materials, together with variable definitions, measurement items, the qualitative coding framework, and de-identified supporting excerpts. Survey and qualitative materials appear in the appendices. Raw qualitative essays are not publicly shared because they contain participant-generated text; de-identified excerpts and the coding framework are provided instead.

## Declaration of generative AI use

The authors used generative AI tools (Claude, Grammarly) to assist with language editing, verification of reported statistics and citations against source data, and reference formatting. The authors reviewed and edited all content and take full responsibility for the published article.

## Ethics declarations

Ethics approval: This study followed the North South University Institutional Review Board (NSU-IRB) research ethics guidelines and was approved by the NSU IRB/Ethics Review Committee (Approval Protocol No. 2025/NSU-OR/IRB/0219). Informed consent was obtained from all participants, who were informed of voluntary participation, confidentiality, and their right to withdraw. All quantitative and qualitative data were anonymised before analysis.

## References

1. Al Zaidy, A. (2024). The impact of generative AI on student engagement and ethics in higher education. *Journal of Information Technology, Cybersecurity, and Artificial Intelligence*, 1(1), 30-38.
2. Alamer, A., Robat, E. S., Shirvan, M. E., & Ryan, R. (2025). Self-Determination Theory and Language Learning: A Multilevel Meta-Analysis. *Educational Psychology Review*, 37(2), 59.
3. Alon-Barkat, S., & Busuioc, M. (2023). Human-AI Interactions in Public Sector Decision Making: "Automation Bias" and "Selective Adherence" to Algorithmic Advice. *Journal of Public Administration Research and Theory*, 33(1), 153-169.

4. An, Q., Yang, J., Xu, X., Zhang, Y., & Zhang, H. (2024). Decoding AI ethics from Users\' lens in education: A systematic review. *Heliyon*, 10(20).
5. Annamalai, N., Bervell, B., Mireku, D. O., & Andoh, R. P. K. (2025). Artificial intelligence in higher education: Modelling students' motivation for continuous use of ChatGPT based on a modified self-determination theory. *Computers and Education: Artificial Intelligence*, 8, 100346.
6. Armstrong, J. S., & Overton, T. S. (1977). Estimating Nonresponse Bias in Mail Surveys. *Journal of Marketing Research*, 14(3), 396-402.
7. Atchley, P., Pannell, H., Wofford, K., Hopkins, M., & Atchley, R. A. (2024). Human and AI collaboration in the higher education environment: opportunities and concerns. *Cognitive Research: Principles and Implications*, 9(1), 20.
8. Bahangulu, J. K., & Owusu-Berko, L. (2025). Algorithmic bias, data ethics, and governance: Ensuring fairness, transparency and compliance in AI-powered business analytics applications. *World J Adv Res Rev*, 25(2), 1746-1763.
9. Baker, R. S., & Hawn, A. (2022). Algorithmic Bias in Education. *International Journal of Artificial Intelligence in Education*, 32(4), 1052-1092.
10. Balaskas, S., Tsiantos, V., Chatzifotiou, S., & Rigou, M. (2025). Determinants of ChatGPT Adoption Intention in Higher Education: Expanding on TAM with the Mediating Roles of Trust and Risk. *Information*, 16(2).
11. Bhattacharjee, A. (2001). Understanding Information Systems Continuance: An Expectation-Confirmation Model. *MIS Quarterly*, 25(3), 351-370.
12. Biswas, M. I., Talukder, M. S., & Chen, Y. (2025). Applying the stimulus-organism-behavior-consequence framework to examine the relationship between intention, usage and recommendation of ChatGPT in higher education. *International Journal of Educational Management*, 39(2), 450-468.
13. Bittle, K., & El-Gayar, O. (2025). Generative AI and Academic Integrity in Higher Education: A Systematic Review and Research Agenda. *Information*, 16(4), 296.
14. Butterfuss, R., Roscoe, R. D., Allen, L. K., McCarthy, K. S., & McNamara, D. S. (2022). Strategy uptake in writing pal: Adaptive feedback and instruction. *Journal of Educational Computing Research*, 60(3), 696-721.
15. Cenfetelli, R. T. (2004). Inhibitors and enablers as dual factor concepts in technology usage. *Journal of the Association for Information Systems*, 5(11), 16.
16. Cetinkaya, N. E., & Krämer, N. (2025). Between transparency and trust: identifying key factors in AI system perception. *Behaviour & Information Technology*, 1-15.
17. Chai, F., Ma, J., Wang, Y., Zhu, J., & Han, T. (2024). Grading by AI makes me feel fairer? How different evaluators affect college students' perception of fairness. *Frontiers in Psychology*, Volume 15 - 2024.
18. Chan, C. K. Y., & Lee, K. K. W. (2025). The balancing act between AI and authenticity in assessment: A case study of secondary school students' use of GenAI in reflective writing. *Computers & Education*, 238, 105399.
19. Chiu, T. K. F., Çoban, M., Sanusi, I. T., & Ayanwale, M. A. (2025). Validating student AI competency self-efficacy (SAICS) scale and its framework. *Educational technology research and development*, 73(4), 2785-2807.
20. Chiu, T. K. F., Falloon, G., Song, Y., Wong, V. W. L., Zhao, L., & Ismailov, M. (2024). A self-determination theory approach to teacher digital competence development. *Computers & Education*, 214, 105017.
21. Chukwuere, J. E., & Chukwuere, G. C. J. (2025). Technostress factors among students in the adoption of Generative Artificial Intelligence (GenAI) in higher education: A rapid review narrative. *International Conference on Emerging Technology and Interdisciplinary Sciences*, 37-45.
22. Corbin, J., & Strauss, A. (2015). *Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory* (4 ed.). Sage Publications.
23. Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: the state of the field. *International Journal of Educational Technology in Higher Education*, 20(1), 22.

24. Cummings, R. E., Monroe, S. M., & Watkins, M. (2024). Generative AI in first-year writing: An early analysis of affordances, limitations, and a framework for the future. *Computers and Composition*, 71, 102827.
25. Dalalah, D., & Dalalah, O. M. A. (2023). The false positives and false negatives of generative AI detection tools in education and academic research: The case of ChatGPT. *The International Journal of Management Education*, 21(2), 100822.
26. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.
27. Dempsey, C., Farrell, E., & McCoy, S. (2025). Understanding the role of school experiences in the wellbeing of girls, SEN and low SES students: A self-determination theory approach. *Studies in Educational Evaluation*, 86, 101489.
28. Dennehy, D., Griva, A., Pouloudi, N., Dwivedi, Y. K., Mäntymäki, M., & Pappas, I. O. (2023). Artificial Intelligence (AI) and Information Systems: Perspectives to Responsible AI. *Information Systems Frontiers*, 25(1), 1-7.
29. Dhillon, P. S., Molaei, S., Li, J., Golub, M., Zheng, S., & Robert, L. P. (2024). *Shaping Human-AI Collaboration: Varied Scaffolding Levels in Co-writing with Language Models* Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems, Honolulu, HI, USA.
30. Dong, X., Tian, Y., & Xi, X. (2025). Exploring the impact of generative artificial intelligence on GAI-driven counterproductive work behavior: an integrated ethical decision-making perspective. *Asia Pacific Journal of Management*.
31. Dwivedi, R., Dave, D., Naik, H., Singhal, S., Omer, R., Patel, P., Qian, B., Wen, Z., Shah, T., Morgan, G., & Ranjan, R. (2023). Explainable AI (XAI): Core Ideas, Techniques, and Solutions. *ACM Comput. Surv.*, 55(9), Article 194.
32. Er, E., Akçapınar, G., Bayazıt, A., Noroozi, O., & Banihashem, S. K. (2025). Assessing student perceptions and use of instructor versus AI-generated feedback. *British Journal of Educational Technology*, 56(3), 1074-1091.
33. Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: a perceived risk facets perspective. *International Journal of Human-Computer Studies*, 59(4), 451-474.
34. Feldman-Maggor, Y., Cukurova, M., Kent, C., & Alexandron, G. (2025). The Impact of Explainable AI on Teachers' Trust and Acceptance of AI EdTech Recommendations: The Power of Domain-specific Explanations. *International Journal of Artificial Intelligence in Education*, 35(5), 2889-2922.
35. Flower, L., & Hayes, J. R. (1981). A Cognitive Process Theory of Writing. *College Composition and Communication*, 32(4), 365-387.
36. Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18(1), 39-50.
37. Fosso Wamba, S. (2022). Impact of artificial intelligence assimilation on firm performance: The mediating effects of organizational agility and customer agility. *International Journal of Information Management*, 67, 102544.
38. Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School Engagement: Potential of the Concept, State of the Evidence. *Review of Educational Research*, 74(1), 59-109.
39. Gligor, D. M., & Autry, C. W. (2012). THE ROLE OF PERSONAL RELATIONSHIPS IN FACILITATING SUPPLY CHAIN COMMUNICATIONS: A QUALITATIVE STUDY. *Journal of Supply Chain Management*, 48(1), 24-43.
40. Glikson, E., & Woolley, A. W. (2020). Human Trust in Artificial Intelligence: Review of Empirical Research. *Academy of Management Annals*, 14(2), 627-660.
41. Golzar, J., Noor, S., & Tajik, O. (2022). Convenience sampling. *International Journal of Education & Language Studies*, 1(2), 72-77.
42. Guan, H., Dong, L., & Zhao, A. (2022). Ethical Risk Factors and Mechanisms in Artificial Intelligence Decision Making. *Behavioral Sciences*, 12(9), 343.
43. Guest, G., Namey, E., & Chen, M. (2020). A simple method to assess and report thematic saturation in qualitative research. *PLOS ONE*, 15(5), e0232076.

44. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2-24.
45. Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer Nature.
46. Han, B., Nawaz, S., Buchanan, G., & McKay, D. (2025). Students' Perceptions: Exploring the Interplay of Ethical and Pedagogical Impacts for Adopting AI in Higher Education. *International Journal of Artificial Intelligence in Education*, 35(4), 1887-1912.
47. Hannah, S. K., Ng, B. L. L., & Liu, W. C. (2024). Fostering student motivation and engagement through teacher autonomy support: A self-determination theory perspective. *International Journal of Instruction*, 17(2), 583-598.
48. Haque, A. K. M. B., Islam, A. K. M. N., & Mikalef, P. (2023). Explainable Artificial Intelligence (XAI) from a user perspective: A synthesis of prior literature and problematizing avenues for future research. *Technological Forecasting and Social Change*, 186, 122120.
49. Hasan, A., Brown, S., Davidovic, J., Lange, B., & Regan, M. (2022). Algorithmic Bias and Risk Assessments: Lessons from Practice. *Digital Society*, 1(2), 14.
50. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115-135.
51. Herzberg, F. I. (1966). *Work and the nature of man*. World.
52. Hew, K. F., Huang, W., Du, J., & Jia, C. (2023). Using chatbots to support student goal setting and social presence in fully online activities: learner engagement and perceptions. *Journal of Computing in Higher Education*, 35(1), 40-68.
53. Hina, M., Azad, N., & Islam, N. (2025). Enablers and inhibitors of AI assimilation in hiring: mitigating the effects of inhibitors through human-AI collaboration. *Information Technology & People*, 38(8), 73-96.
54. Hoffman, R. R., Mueller, S. T., Klein, G., & Litman, J. (2023). Measures for explainable AI: Explanation goodness, user satisfaction, mental models, curiosity, trust, and human-AI performance [Review]. *Frontiers in Computer Science*, Volume 5 - 2023.
55. Hoffmann, E. A. (2007). Open-Ended Interviews, Power, and Emotional Labor. *Journal of Contemporary Ethnography*, 36(3), 318-346.
56. Hofmann, B. (2025). Biases in AI: acknowledging and addressing the inevitable ethical issues [Review]. *Frontiers in Digital Health*, Volume 7 - 2025.
57. Holstein, K., De-Arteaga, M., Tumati, L., & Cheng, Y. (2023). Toward Supporting Perceptual Complementarity in Human-AI Collaboration via Reflection on Unobservables. *Proc. ACM Hum.-Comput. Interact.*, 7(CSCW1), Article 152.
58. Ilker, E., Sulaiman Abubakar, M., & Rukayya Sunusi, A. (2015). Comparison of Convenience Sampling and Purposive Sampling. *American Journal of Theoretical and Applied Statistics*, 5(1), 1-4.
59. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577-586.
60. Johnson, M. S., Liu, X., & McCaffrey, D. F. (2022). Psychometric Methods to Evaluate Measurement and Algorithmic Bias in Automated Scoring. *Journal of Educational Measurement*, 59(3), 338-361.
61. Jones-Jang, S. M., & Park, Y. J. (2023). How do people react to AI failure? Automation bias, algorithmic aversion, and perceived controllability. *Journal of Computer-Mediated Communication*, 28(1), zmac029.
62. Karagoz, I. (2025). AI-Generated Feedback in English Writing Instruction for Language Learners: A Systematic Review. *THE READING MATRIX*, 25, 51-67.
63. Kaur, H., & Pavlova, M. (2026). Machine-assisted thematic mapping of AI in education discourse: Systematic review from 2005–2024. *Humanities and Social Sciences Communications*, 13, Article 991. <<https://doi.org/10.1057/s41599-026-07342-5>>

64. Kbaier, E., Salminen, J., & Jansen, B. J. (2025). "A glimpse into the AI": exploring the effect of consumers' chatbot interaction experience on brand attachment and advocacy with the moderating role of AI skepticism. *Asia-Pacific Journal of Business Administration*, 1-26.
65. Khalifa, M., & Albadawy, M. (2024). Using artificial intelligence in academic writing and research: An essential productivity tool. *Computer Methods and Programs in Biomedicine Update*, 5, 100145.
66. Kim, J., Lee, H., & Cho, Y. H. (2022). Learning design to support student-AI collaboration: perspectives of leading teachers for AI in education. *Education and Information Technologies*, 27(5), 6069-6104.
67. Kock, N. (2015). Common Method Bias in PLS-SEM: A Full Collinearity Assessment Approach. *International Journal of e-Collaboration (IJeC)*, 11(4), 1-10.
68. Kohnke, L., Zou, D., & Moorhouse, B. L. (2024). Technostress and English language teaching in the age of generative AI. *Educational Technology & Society*, 27(2), 306-320.
69. Kordzadeh, N., & Ghasemaghaei, M. (2022). Algorithmic bias: review, synthesis, and future research directions. *European Journal of Information Systems*, 31(3), 388-409.
70. Krook, J. (2025). When autonomy breaks: the hidden existential risk of AI. *AI & SOCIETY*, 40(8), 6011-6024.
71. Lapointe, L., & Rivard, S. (2005). A Multilevel Model of Resistance to Information Technology Implementation. *MIS Quarterly*, 29(3), 461-491.
72. Lewicki, R. J., McAllister, D. J., & Bies, R. J. (1998). Trust and distrust: New relationships and realities. *Academy of Management Review*, 23(3), 438-458.
73. Li, S. (2025). Generative AI and Second Language Writing. 2(1), 122-152. (Digital Studies in Language and Literature)
74. Li, Y., Wu, B., Huang, Y., & Luan, S. (2024). Developing trustworthy artificial intelligence: insights from research on interpersonal, human-automation, and human-AI trust. *Front Psychol*, 15, 1382693.
75. Limayem, M., Cheung, C., & Chan, G. (2003). Explaining information systems adoption and post-adoption: toward an integrative model. *International Conference on Information Systems*,
76. Liu, C., & Correia, A.-P. (2021). A Case Study of Learners' Engagement in Mobile Learning Applications. *Online Learning*, 25(4), 25-48.
77. Lund, B. D., Lee, T. H., Mannuru, N. R., & Arutla, N. (2025). AI and Academic Integrity: Exploring Student Perceptions and Implications for Higher Education. *Journal of Academic Ethics*.
78. Luo, L., & Yusuf, A. (2025). Bridging AI and pedagogy: how AI-adaptive feedback shapes Chinese EFL students' writing engagement, metacognitive writing strategies, and writing performance. *Assessment & Evaluation in Higher Education*, 1-24.
79. Martin, K., & Waldman, A. (2023). Are Algorithmic Decisions Legitimate? The Effect of Process and Outcomes on Perceptions of Legitimacy of AI Decisions. *Journal of Business Ethics*, 183(3), 653-670.
80. McCarthy, K. S., Roscoe, R. D., Allen, L. K., Likens, A. D., & McNamara, D. S. (2022). Automated writing evaluation: Does spelling and grammar feedback support high-quality writing and revision? *Assessing Writing*, 52, 100608.
81. Mekheimer, M. (2025). Generative AI-assisted feedback and EFL writing: a study on proficiency, revision frequency and writing quality. *Discover Education*, 4(1), 170.
82. Memarian, B., & Doleck, T. (2023). Fairness, Accountability, Transparency, and Ethics (FATE) in Artificial Intelligence (AI) and higher education: A systematic review. *Computers and Education: Artificial Intelligence*, 5, 100152.
83. Negm, E. (2026). Artificial intelligence (AI) usage in higher education: Technology integration into curriculums to attain UN sustainable development goals. *Journal of Applied Research in Higher Education*, 18(2), 616–631.  
<https://doi.org/10.1108/JARHE-04-2025-0275>
84. Nguyen, A., Hong, Y., Dang, B., & Huang, X. (2024). Human-AI collaboration patterns in AI-assisted academic writing. *Studies in Higher Education*, 49(5), 847-864.

85. Nicol, D. J., & Macfarlane-Dick, D. (2006). Formative assessment and self-regulated learning: a model and seven principles of good feedback practice. *Studies in Higher Education*, 31(2), 199-218.
86. Nizette, F., Hammedi, W., van Riel, A. C. R., & Steils, N. (2024). Why should I trust you? Influence of explanation design on consumer behavior in AI-based services. *Journal of Service Management*, 36(1), 50-74.
87. Okamura, K., & Yamada, S. (2020). Adaptive trust calibration for human-AI collaboration. *PLOS ONE*, 15(2), e0229132.
88. Olafsen, A. H., Marescaux, B. P. C., & Kujanpää, M. (2025). Crafting for autonomy, competence, and relatedness: A self-determination theory model of need crafting at work. *Applied Psychology*, 74(1), e12570.
89. Omughelli, D., Gordon, N., & Al Jaber, T. (2024). Fairness, Bias, and Ethics in AI: Exploring the Factors Affecting Student Performance. *Journal of Intelligent Communication*, 3(2), 100-110.
90. Orlikowski, W. J. (1992). The Duality of Technology: Rethinking the Concept of Technology in Organizations. *Organization Science*, 3(3), 398-427.
91. Palash, M. A. S., Talukder, M. S., Islam, A. K. M. N., & Bao, Y. (2022). Positive and negative valences, personal innovativeness and intention to use facial recognition for payments. *Industrial Management & Data Systems*, 122(4), 1081-1108.
92. Pan, M., Lai, C., & Guo, K. (2025). AI chatbots as reading companions in self-directed out-of-class reading: A self-determination theory perspective. *British Journal of Educational Technology*, n/a(n/a).
93. Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, 7(3), 101-134. \<Go to ISI\>://WOS:000182935400005
94. Pikhart, M., & Al-Obaydi, L. H. (2025). Reporting the potential risk of using AI in higher Education: Subjective perspectives of educators. *Computers in Human Behavior Reports*, 18, 100693.
95. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of applied psychology*, 88(5), 879.
96. Rai, A., Constantinides, P., & Sarker, S. (2019). Editor's Comments: Next-Generation Digital Platforms: Toward Human--AI Hybrids. *Management Information Systems Quarterly*, 43(1), iii-ix.
97. Razmerita, L. (2024). Human-AI collaboration: A student-centered perspective of generative AI use in higher education. European Conference on e-Learning,
98. Rosenbacke, R., Melhus, Å., McKee, M., & Stuckler, D. (2024). How Explainable Artificial Intelligence Can Increase or Decrease Clinicians' Trust in AI Applications in Health Care: Systematic Review. *JMIR AI*, 3, e53207.
99. Ryan, M., & Stahl, B. C. (2020). Artificial intelligence ethics guidelines for developers and users: clarifying their content and normative implications. *Journal of Information, Communication and Ethics in Society*, 19(1), 61-86.
100. Ryan, R., & Deci, E. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American psychologist*, 55(1), 68.
101. Sankaran, S., Zhang, C., Aarts, H., & Markopoulos, P. (2021). Exploring Peoples\' Perception of Autonomy and Reactance in Everyday AI Interactions [Original Research]. *Frontiers in Psychology*, Volume 12 - 2021.
102. Sebopelo, P., Baloyi, O., & Chukwuma, N. N. (2025). Artificial Intelligence assimilation and University Service Quality: The Mediating Role of student satisfaction. *Review of Artificial Intelligence in Education*, 6(i), e042.
103. Shin, D. (2020). User Perceptions of Algorithmic Decisions in the Personalized AI System: Perceptual Evaluation of Fairness, Accountability, Transparency, and Explainability. *Journal of Broadcasting & Electronic Media*, 64(4), 541-565.
104. Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies*, 146, 102551.
105. Shneiderman, B. (2020). Human-Centered Artificial Intelligence: Reliable, Safe & Trustworthy. *International Journal of Human-Computer Interaction*, 36(6), 495-504.

106. Sperber, L., MacArthur, M., Minnillo, S., Stillman, N., & Whithaus, C. (2025). Peer and AI Review + Reflection (PAIRR): A human-centered approach to formative assessment. *Computers and Composition*, 76, 102921.
107. Srinivasan, R., & San Miguel González, B. (2022). The role of empathy for artificial intelligence accountability. *Journal of Responsible Technology*, 9, 100021.
108. Stratton, S. J. (2023). Population Sampling: Probability and Non-Probability Techniques. *Prehospital and Disaster Medicine*, 38(2), 147-148.
109. Strauss, A., & Corbin, J. (1998). *Basics of qualitative research: Techniques and procedures for developing grounded theory*, 2nd ed. Sage Publications, Inc.
110. Swanson, E. B. (2004). How is an IT innovation assimilated. IFIP Working Conference on IT Innovation for Adaptability and Competitiveness,
111. Talukder, M. S., Islam, Q. T., & Karim, Z. (2024). Facilitators and inhibitors of attitude and word-of-mouth intention toward adoption of digital municipal service systems: A stimulus-organism-response approach. *PLOS ONE*, 19(12), e0315009.
112. Talukder, M. S., Laato, S., Islam, A. K. M. N., & Bao, Y. (2021). Continued use intention of wearable health technologies among the elderly: an enablers and inhibitors perspective. *Internet Research*, ahead-of-print(ahead-of-print).
113. Teng, M. F., & Yue, M. (2023). Metacognitive writing strategies, critical thinking skills, and academic writing performance: A structural equation modeling approach. *Metacognition and Learning*, 18(1), 237-260.
114. Tsamados, A., Aggarwal, N., Cows, J., Morley, J., Roberts, H., Taddeo, M., & Floridi, L. (2022). The ethics of algorithms: key problems and solutions. *AI & SOCIETY*, 37(1), 215-230.
115. Tseng, H., Yi, X., & Cunningham, B. (2022). Learning technology acceptance and continuance intention among business students: The mediating effects of confirmation, flow, and engagement. *Australasian Journal of Educational Technology*, 38(3), 70-86.
116. Türkmen, G. (2024). The Review of Studies on Explainable Artificial Intelligence in Educational Research. *Journal of Educational Computing Research*, 63(2), 277-310.
117. Vaccaro, M., Almaatouq, A., & Malone, T. (2024). When combinations of humans and AI are useful: A systematic review and meta-analysis. *Nature Human Behaviour*, 8(12), 2293-2303.
118. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478.
119. Vollbrecht, L. A. (2022). Why We Need Skepticism in Argument: Skeptical Engagement as a Requirement for Epistemic Justice. *Argumentation*, 36(2), 269-285.
120. von Zahn, M., Liebich, L., Jussupow, E., Hinz, O., & Bauer, K. (2025). Knowing (Not) to Know: Explainable Artificial Intelligence and Human Metacognition. *Information Systems Research*.
121. Wang, B., Yuan, T., & Rau, P.-L. P. (2024). Effects of Explanation Strategy and Autonomy of Explainable AI on Human-AI Collaborative Decision-making. *International Journal of Social Robotics*, 16(4), 791-810.
122. Wang, C. (2025). Exploring Students' Generative AI-Assisted Writing Processes: Perceptions and Experiences from Native and Nonnative English Speakers. *Technology, Knowledge and Learning*, 30(3), 1825-1846.
123. Wang, Z., Li, M., & Islam, A. A. (2026). Reimagining teacher-AI co-design in learning task design: Trends and perspectives. *Humanities and Social Sciences Communications*, 13, Article 757. <<https://doi.org/10.1057/s41599-026-06981-y>>
124. Wang, X., Xie, F., Cheng, G., & Shehzadi, K. (2025). Identifying and assessing the risks of artificial intelligence applications in smart libraries: Perspective of technostress. *Information Development*, 02666669251329032.
125. Xia, Q., Chiu, T. K. F., & Chai, C. S. (2023). The moderating effects of gender and need satisfaction on self-regulated learning through Artificial Intelligence (AI). *Education and Information Technologies*, 28(7), 8691-8713.

126. Yang, D., Liu, J., Wang, H., Chen, P., Wang, C., & Metwally, A. H. S. (2025). Technostress among teachers: A systematic literature review and future research agenda. *Computers in Human Behavior*, 168, 108619.

127. Yu, T., Tian, Y., Chen, Y., Huang, Y., Pan, Y., & Jang, W. (2025). How Do Ethical Factors Affect User Trust and Adoption Intentions of AI-Generated Content Tools? Evidence from a Risk-Trust Perspective. *Systems*, 13(6).

128. Zerilli, J., Bhatt, U., & Weller, A. (2022). How transparency modulates trust in artificial intelligence. *Patterns*, 3(4).

129. Zerilli, J., Knott, A., Maclaurin, J., & Gavaghan, C. (2019). Algorithmic Decision-Making and the Control Problem. *Minds and Machines*, 29(4), 555-578.

130. Zhang, T., & Tong, Q. (2025). The Technostress of ChatGPT Usage: How Do Perceived AI Characteristics Affect User Discontinuous Usage Through AI Anxiety and User Negative Attitudes? *International Journal of Human-Computer Interaction*, 41(16), 9918-9929.

131. Zhou, Q., Suraworachet, W., Celiktutan, O., & Cukurova, M. (2022). What Does Shared Understanding in Students' Face-to-Face Collaborative Learning Gaze Behaviours "Look Like"? Artificial Intelligence in Education, Cham.

132. Zhu, W., Huang, L., Zhou, X., Li, X., Shi, G., Ying, J., & Wang, C. (2025). Could AI Ethical Anxiety, Perceived Ethical Risks and Ethical Awareness About AI Influence University Students' Use of Generative AI Products? An Ethical Perspective. *International Journal of Human-Computer Interaction*, 41(1), 742-764.

Figures

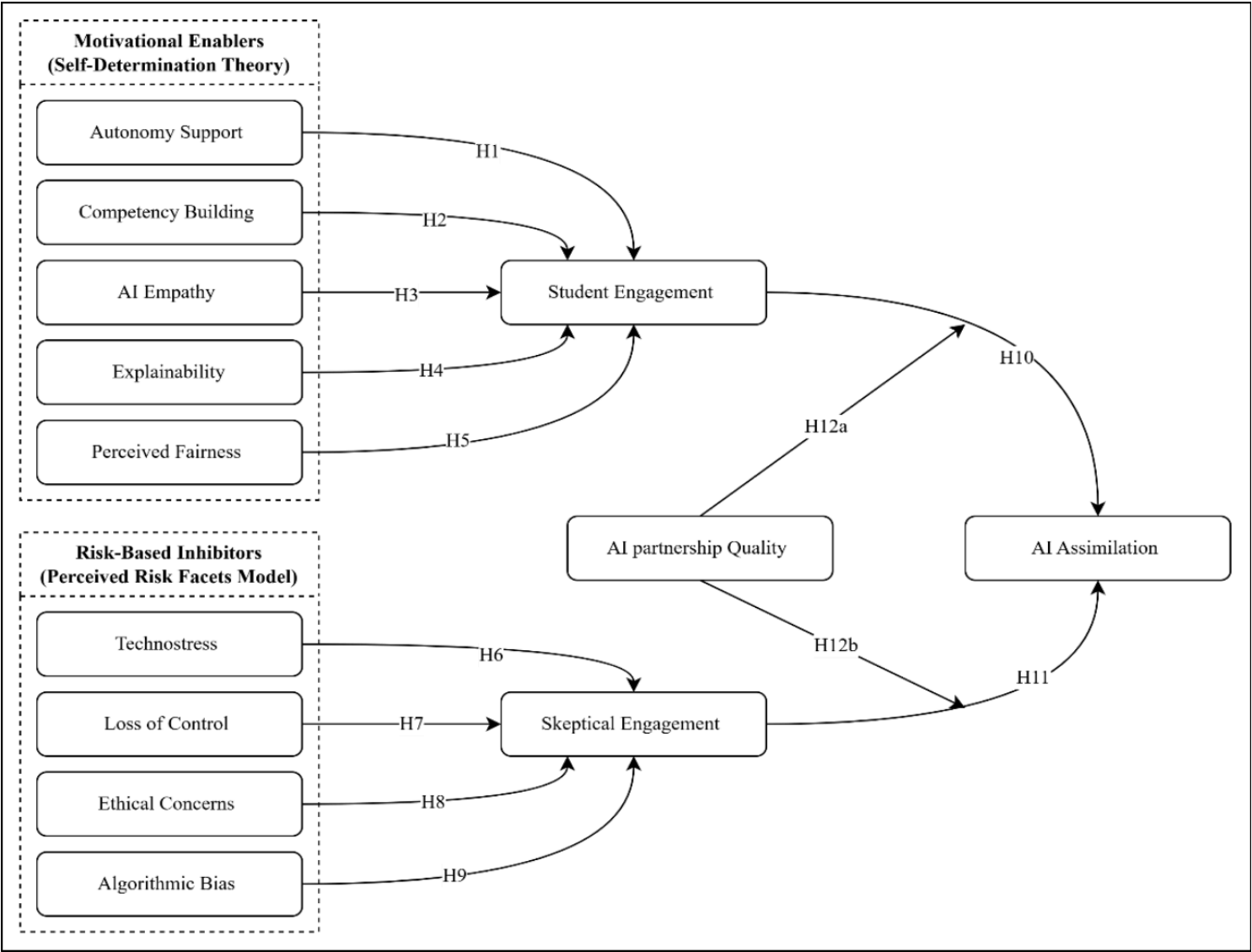


Figure 1

Proposed research model.

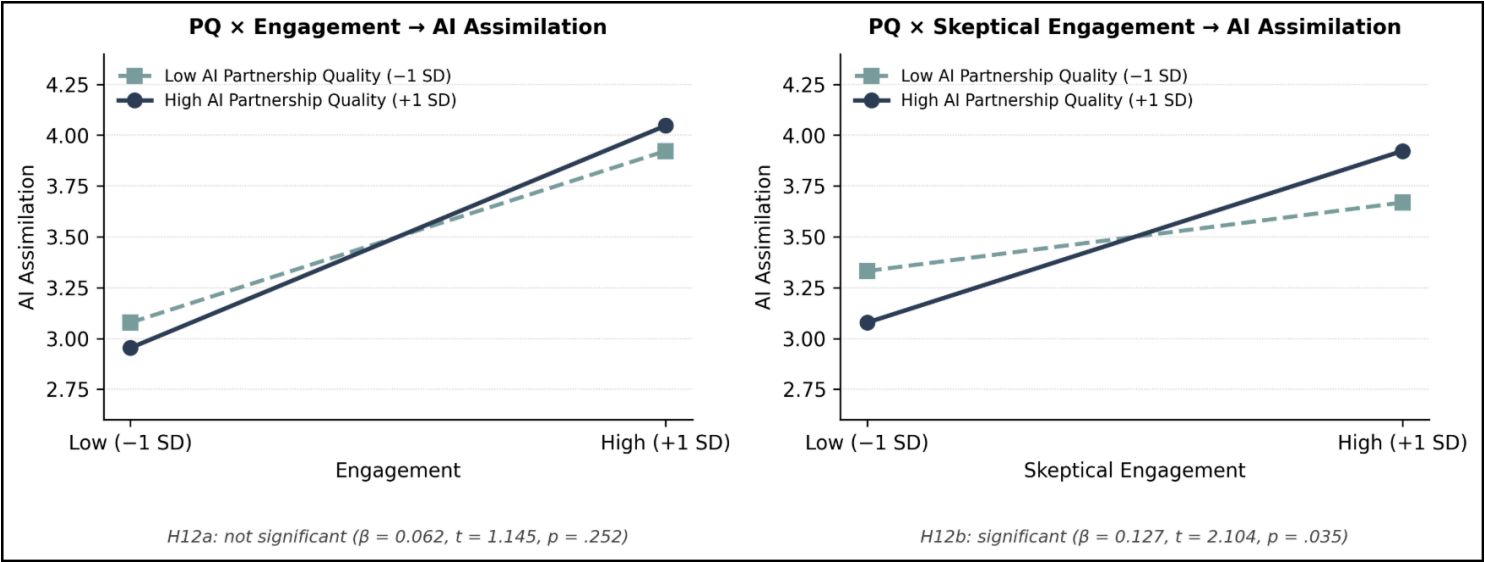


Figure 2

Simple slopes for the moderating effect of AI Partnership Quality (PQ), plotted at  $\pm 1$  SD of the focal predictor and moderator.

## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [AppendixRevised.docx](#)